# “Quantifying Cognitive Workload and Assessing the Effect of Mindfulness Interventions using EEG and other Biosignals”

Submitted in partial fulfilment of the requirement of the degree of

## Doctor of Philosophy


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## (2019PEC202)

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## 1. Introduction:

Synchronized synaptic activity of cortical neurons ascends Electroencephalography (EEG). EEG is the electrical activity in brain, where voltage fluctuation is observed due to flow of ionic current. Ionic current is a result of firing of neurons inside brain. Physiological signals like EEG is important tool to study neurocognitive processes [25]. High temporal resolution technique like EEG capture occurred cognition in time frame of cognitive dynamics. Event-related potential (ERP) is measurement of the brain's response to a stimulus. The EEG can monitor cognitive processes occurring within milliseconds range, again the EEG signal is multidimensional.

An EEG is important tool for diagnostic tests of epilepsy and seizures. It is also helpful to diagnose other brain abnormalities like tumors, stroke etc. Various clinical applications uses EEG as a tool for sleep stages classification, anesthesia depth measurement , brain injury and abnormal brain states detection. Unlike MRI and CT, an EEG has high millisecond-range temporal resolution.

An EEG signal has amplitude in microvolt range, and frequency bands of EEG extends from 0.1 Hz to 40.0 Hz, Study of higher frequency above 30 Hz is difficult as they are attenuated by skull and scalp layers. Again, higher frequencies are overshadowed by muscular artifacts. Within the usable frequency band, choice of sub-band to be analyzed is always application specific [19]. Various sub-bands of interest are as follows:

**Delta:** Frequency below 4 Hz. It is dominant in children during sleep.

**Theta:** Frequency range of 4-7 Hz. Physiological state characterizes as visual imagery, light sleep.

**Alpha**: Frequency range of 8-12 Hz. Physiological state characterizes as awake, non-focused, relaxed.

**Beta:** Frequency range of 13-30 Hz. Physiological state characterizes as awake, alert, focused attention and problem solving.

**Gamma:** Frequency above 30 Hz. Physiological state characterizes as consciousness and memory related task.

An EEG system tracks and records brain wave patterns by placing electrodes on the scalp. Two system of electrodes placement on the scalp:

a) 10-20 international system: 21 electrodes
b) 10-10 international system: 64 electrodes [18].

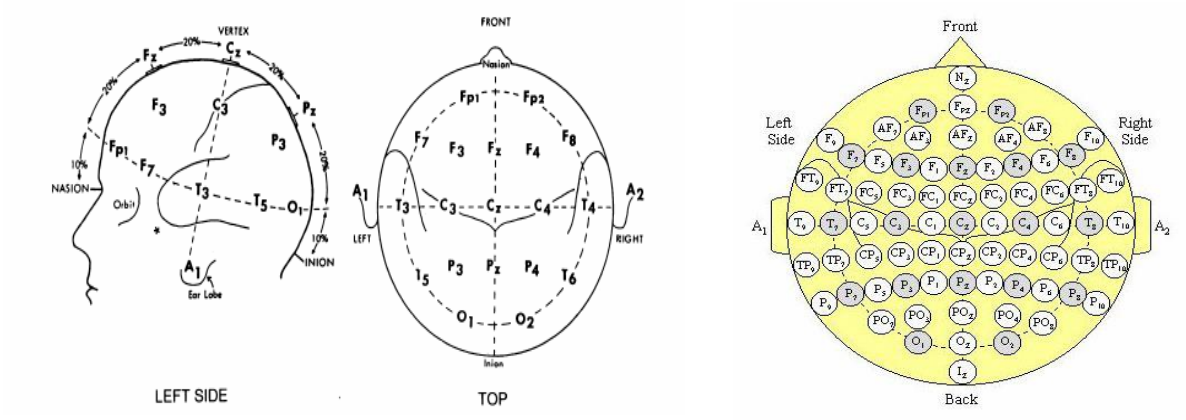


Fig1. a) 10-20 international system b) 10-10 international system

In conventional EEG, electrodes monitor electrical activity of brain from outside the skull and in intracranial EEG, electrodes are implanted over brain surface through surgery.

Two halves of the cerebrum are called hemispheres. Each hemisphere is divided into lobes:

**Frontal lobe**: As shown in Fig. 2 they can be seen in front part of the brain. Motor skills, problem solving, judgment, planning, and attention all these high-level skills are coordinated by frontal lobe. They also manage emotions and impulse control.

**Parietal lobe**: They can be seen behind the frontal lobes. Sensory information from other parts of the brain is organized and interpreted by parietal lobe.

**Temporal lobe**: They can be seen at the level of ears. Visual memory, verbal memory coordination and interpretation of the emotions are done by temporal lobe.

**Occipital lobe**: They can be seen at back of the brain. Aspects of vision like identify and read words, is handled by occipital lobe.

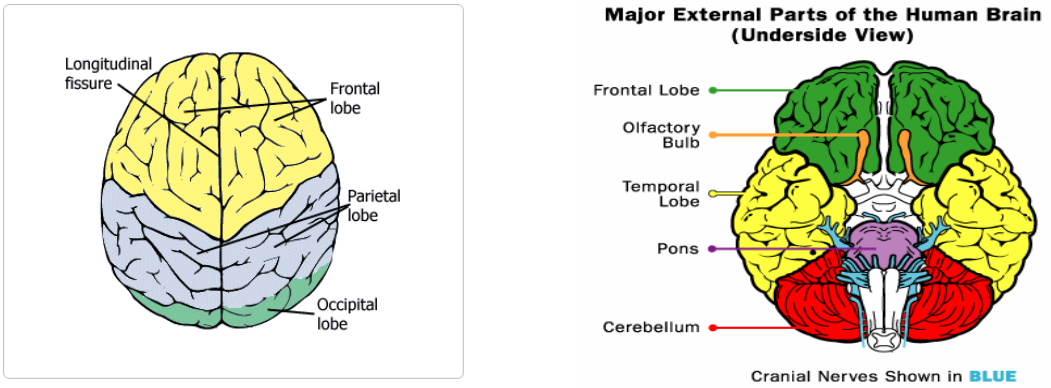


Fig 2. Brian Lobes

Logical and orderly arrangements of channels (electrode pairs) referred to as montage. There are two basic types of EEG montage:

a) Referential: A common reference electrode is used with every channel. An active electrode and an inactive reference electrode are involved in measurement of potential.

b) Bipolar: Two electrodes per channel, so every channel has reference electrode. Two active electrodes are involved in measurement of potential.

Cognitive processes referred to the mental processes involved in gaining knowledge and comprehension. These processes include thinking, knowing, remembering, judging, and problem-solving. These higher-level functions of the brain cover language, imagination, perception, and planning.

There are many different types of cognitive processes. These include:

**Attention**: It allows to engross a specific stimulus.

**Language**: It allows to understand and express thoughts. It helps in communication.

**Learning**: It synthesises information with some inputs and integrate it with prior knowledge.

**Memory**: It allows to encode, store, and retrieve information. Also helps to retain knowledge.

**Perception**: Sensation is used to acquire information and accordingly response is generated for interaction.

**Thought**: It is an ability of decision-making, problem-solving, and logical reasoning.

There are two types of memories associated with human brain: Working Memory and long-term memory. When individual is exposed to a new information, it is held and processed in working memory. Making connection between working and long-term memory will allow you to learn new things.

Cognitive load is related to limited capacity of working memory. Processing too much information at once can lead to cognitive work overload for working memory. This overload slows down the learning process. Focused attention helps to curtail redundancy and split attention effects related to working memory and will help to learn in an integrated environment. Single modality or multimodal approaches are used for assessment of cognitive workload. However, classifying cognitive states is challenging, physiological signals help in identification and quantification of cognitive dynamics in prescribed time frame [21].

Maintaining the best level of cognitive load during learning process is of utmost importance. Cognitive dynamics is important aspect of cognitive load theory (CLT). CLT is an instructional design theory that reflects cognitive architecture [23].

## 2. Related Literature Review:

In 2007, Deiber and group proposed a study for oscillatory brain dynamics in relation to working memory. Control task were designed to study oscillatory dynamics after application of stimulus with focused attention [16].

[15] discussed evoked potential in steady state and studied interactions between task and distractor stimuli. [14] investigated amplitude and phase dynamics in the alpha

band. [13] discussed seven levels of load for cognitive task discrimination using EEG. Wavelet coefficients extracted from segmented EEG. [12] assessed memory workload using EEG in the n-Back Task and reported classification accuracy around 80%. [11] investigated neurophysiological features using EEG for operators task performance. Feature extraction is done using Laplacian Eigenmap, SVM classifier is used for classification. [10] carried assessment of alertness level of an individual using multimodal physiological signal. Also, quantification of alertness is done through fusing information into single metric. [9] done assessment of cognitive load for learning in multimedia environment using EEG. [8] analyzed readability for cognitive load Assessment. Physiological signals like EEG and pupillary response are used to address both global and localized analysis of a content. [7] carried assessment of high cognitive load. Wireless EEG is used for data collection. Also done validation of a Modified *N*-Back (1-back, 2-back) Task. Feasibility of system is tested to differentiate among three levels of cognitive task load in a simulator study. [6] proposed attention level detection by using quantitative evaluation formula. Blink rates and pupillometry are used along with EEG, ECG, and NIRS in the experimentation. Proposed system met an accuracy of 82.31 %. [5] carried fusing of features showing opposite variation trend with increase in memory load levels and studied the feasibility of this fusion. Fusion framework is based on EEG. [24] proposed feature extraction of EEG by decomposing signal using DWT and combined with EMD decomposition for sub band frequencies along with approximate entropy. [4] discussed EEG based workload estimation with 3D Convolutional Neural Network employing a Multilevel Feature Fusion algorithm. Performance of the network was verified with Sternberg task, which measure the mental workload of the participant. Accuracy achieved with their trained network is 90.8 %, and with public EEG dataset accuracy achieved is 93.9 %. [3] explored association rule mining to find correlation between attention and cognitive load. Non-invasive EEG measuring instrument is used to get data for experimentation. The subjects' maximum attention and minimum attention values were evaluated with designed experimentation. [2] presented a new deep learning Unsupervised Domain Adaptation D-UDA method as Custom Domain Adaptation (CDA) for cognitive load recognition of cross subjects using EEG. [1] Presented a review on multimodal fusion for objective assessment of cognitive workload. This review discussed about need of improvement of the estimation accuracy of cognitive workload. Here existing studies carried using various sensor technologies was compared with single modality and robust multimodal

approaches. Also, synthesis of main findings of published studies related to multimodal data fusion to estimate the cognitive workload were presented.

## 3. Methodology for Research:

Inspired by the work carried out in above literature, following methodology is proposed for Research work:

- Physiological signal like EEG is suitable for analyses, assessment of individual and group can be carried out.
- Preprocessing of raw EEG data is necessary and useful for advanced analysis.
- In order to analyse features of cognitive workload using EEG many intermediate steps must be performed: artefact removal, signal normalization and segmentation, feature extraction, and classification [20].
- It is recommended to use high pass filter at 0.5 Hz, which minimizes slow drifts. A notch filters at 50 Hz or 60 Hz help to attenuate electrical line noise. Time frequency decomposition methods like wavelet convolution, FFT, filter-Hilbert involve application of set of temporal filters to data.
- Spatial filtering is applied to data because of following reasons:
  1) It helps in the localization of result. 2) it allows us to isolate topographical feature of the data. 3) It is one of the processing steps in connectivity analysis.
- For the analysis of resulting data, computations will be carried in time domain, frequency domain and time-frequency domain for each channel [22].

  The currently used features are:

$$power(P_e) = \frac{1}{samples}\sum_{-\infty}^{\infty}\left|eeg(t)\right|^2 ,$$

$$mean(\mu_e) = \frac{1}{samples}\sum_{1}^{samples} eeg(t),$$

$$std.deviation(\sigma_e) = \sqrt{\frac{1}{samples}\sum_{1}^{samples}\left(eeg(t)-\mu_e\right)^2} ,$$

  where *eeg (t)* represent single channel in time domain.

Baseline normalization is very important to interpret the dynamics correctly. Baseline normalization transforms all data to the same scale which is numerically interpretable. It disentangles task-related data from background activity. Also, normalization provides data which is more likely to be normally distributed.

A mathematical procedure called convolution, which in turn relies on dot product is used for extracting frequency information from a time-domain signal.

$$a \cdot b = \sum_{i=1}^{n} a_i b_i$$

where a and b are vectors of same length and n is number of elements in a.

The Fourier transform resulted in three-dimensional representation of time series EEG data, where tree dimensions are frequency, power and phase. In frequency domain band power is very important feature of EEG. FFT is used for calculation.

Below is the formula for the discrete Fourier transform of variable *x*.

$$X_k = \sum_{n=0}^{N-1} x_n e^{-2\pi i k n / N}$$

In which n is number of data points in vector *x*, and 0<= *k*<=1

Fourier transform uses sine wave as a kernel, and it does not have temporal localization, that is why it is unable to show change in frequency characteristics over time [20].

For non-stationary EEG signal, Wavelet Transform decomposition is more suitable to work with time-frequency domain which can give dynamical change information [17]. Wavelet finds a trade- off between temporal precision and frequency precision. Dot product between signal and kernel is producing a waiting function. Convolution can be implemented and conceptualize in two different ways, in time domain and frequency domain. In order to get exact result of convolution where result signal is of same length of signal then zero padding must be done at beginning and end of signal before convolution.

Three steps of wavelet convolution are: 1) Take FFT of signals (EEG data and wavelet) 2) Multiply Fourier spectra 3) Take inverse FFT

Below is the formula for inverse Fourier Transform.

$$x_n = \frac{1}{N} \sum_{k=0}^{N-1} X_k e^{2\pi i k n / N}.$$

Feature extraction from EEG is done by adopting Discrete wavelet transform (DWT). Various features extracted are energy, entropy, Min, Max, Mean, Median, Standard deviation, Variance, Skewness Root mean square (RMS), relative wave energy (RWE), recursive energy efficiency (REE) etc.

$$RMS(j) = \sqrt{\frac{\sum_{i=1}^{j} \sum_{ni} D_i(n)^2}{\sum_{i=1}^{j} n_i}}, \quad REE = \frac{E_{band}}{E_{\alpha\beta\gamma}}$$

where $D_i$ are the detail coefficients, $n_i$ the number of $D_i$ *at* the *i*th decomposition level, and *j* denotes the number of levels; $E_{band}$ is the sub band energy, and $E_{\alpha\beta\gamma}$ is the total energy of sub bands ( $E_\alpha + E_\beta + E_\gamma$ ).

By finding correlation among various features complex signal analysis will be done.

Machine learning tool has tremendous ability to handle complex data sets and are important for discovering information in a complex data set. In classification step labels are assigned to a set of features (the feature vector) extracted from the signals. These labels are classes corresponds to the kind of relation state identified. A classifier is trained for each class (e.g., positive/negative) to provide an indication of whether it does or does not belong to that specific class. K-Nearest Neighbor, Artificial Neural Networks/Deep Learning, Perceptron, Decision Tree, Logistic Regression, Support Vector Machine (SVM), Naive Bayes, Linear Discriminant Analysis, Fisher's discriminant analysis, Empirical mode Decomposition, and Single Trial Classification serves as the classifier. The best

classifier for cognitive task recognition using EEG can be found by comparing and studying the various classifier combinations.

## 4. Proposed Research Work:

Study systematic comparison of EEG and other biosignal features related to cognitive workload. And propose novel techniques to improve learn-ability of youth through training. Hence it is decided to pursue following objectives:

1. To evolve a few novel features to quantify cognitive workload and how cognitive workload varies with time and complexity of task will be studied in detail.
2. To assess the scaling effect of cognitive workload on learn-ability through mindfulness intervention.
3. To design better learning techniques, which improve learning ability of an individual through focused attention.

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